# The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis


Wolfram Schlenker
Department of Agricultural and Resource Economics
University of California, Berkeley
207 Giannini Hall #3310
Berkeley, CA 94720 (USA)
email: schlenker@are.berkeley.edu

W. Michael Hanemann
Department of Agricultural and Resource Economics
University of California, Berkeley
207 Giannini Hall #3310
Berkeley, CA 94720 (USA)
email: hanemann@are.berkeley.edu

Anthony C. Fisher
Department of Agricultural and Resource Economics
University of California, Berkeley
207 Giannini Hall #3310
Berkeley, CA 94720 (USA)
email: fisher@are.berkeley.edu



September 14, 2002

**Abstract**

One of the most vulnerable sectors to a change in climatic conditions is agriculture, where climatic variables such as temperature and precipitation are direct inputs into the production function. Previous studies of the potential impact of global warming on U.S. agriculture have yielded widely varying results, with some predicting large damages and others suggesting that U.S. agriculture may even benefit, in at least one likely scenario associated with a doubling of greenhouse gas concentrations. In this paper we show that much, if not all, of the difference in estimates can be explained by the failure to adequately allow for differences between rain-fed and irrigated agriculture, and proximity to urban areas, in the estimation of the relationship between farmland values and climatic and other variables.

A cross-sectional data set of counties in the continental U.S. is employed to estimate a hedonic value function. We first model the error term structure and show that our derived set of weights is best at explaining the heteroscedasticity and spatial correlation of the error terms. Second, we use bootstrap simulations to assess the variability of the damage estimator. Third, Chow tests and a Bayesian outlier analysis show that irrigated and urban counties severely bias the damage estimator. When we limit the analysis to dryland and non-urban counties, the different damage estimators from previous studies overlap and the confidence intervals are cut by up to half. Dryland U.S. agriculture is unambiguously damaged under the $CO_2$ doubling scenario, and the damages are quite large relative to recent estimates in the literature.

We gratefully acknowledge comments on an earlier draft by John (Mac) Callaway, Michael Greenstone, Guido Imbens, George Judge, Robert Mendelsohn, William Nordhaus, and Arnold Zellner and participants at the National Bureau of Economic Research Summer Institute in Environmental Economics. We also wish to thank Robert Mendelsohn for providing us with data used in the estimations. Partial financial support was received from the Institute for Business and Economic Research at the University of California at Berkeley and the Giannini Foundation of Agricultural Economics.

# 1 Introduction

The debate on global climate change began about thirty years ago when climate scientists first speculated that there may be a relationship between increased greenhouse gas concentrations and global warming. In 1990, the Intergovernmental Panel on Climate Change corroborated this finding, stating that is "certain [that] ... there is a natural greenhouse effect which already keeps the Earth warmer than it would otherwise be ... [and that the] emissions resulting from human activities are substantially increasing the atmospheric concentrations of greenhouse gasses" (IPCC, (1990)). In response to such assertions, more than 150 governments attending the Rio Earth Summit in 1992 signed the Framework Convention on Global Climate change. Article 2 of this Convention states that the "ultimate objective of this Convention ... is to achieve ... stabilization of greenhouse gas concentrations that would prevent dangerous anthropogenic interference with the climate system." However, ten years later, the big question still remains how "dangerous" are the consequences of anthropogenic interference, and how much "stabilization" is justified. This has been the subject of an active debate in the economics literature on the potential impacts of climate change on the U.S. economy.[1] Two features of this debate are noteworthy. First, agriculture has been the single largest component of most previous climate change assessments for the U.S. economy. Second, there is more disagreement about the impact on agriculture than any other sector of the U.S. economy.

The first comprehensive studies of the impacts of climate change on the U.S. economy found agriculture to have a large potential for damages. However, more recent studies have contended that the earlier work was methodologically flawed and that a correct analysis shows a much smaller economic loss, or even a gain to U.S. agriculture. For example, Cline (1992) estimated the annual damage to U.S. agriculture (both producers and consumers) from a doubling of greenhouse gas concentrations, based on 1990 conditions, at $17.5 billion in 1990 dollars and Fankhauser (1995) estimated it at $8.4 billion. The recent U.S. National

Assessment estimated that climate change will cost U.S. producers from about \$0.1 up to \$4.2 billion in 1990 dollars, depending on the climate change scenario and the time period considered (Reilly, ed 2002), and Mendelsohn and Neumann (1999) estimated that a doubling of greenhouse gas concentrations will cause an annual net *gain* for U.S. producers amounting to \$24.3 billion.[2] Agriculture has thus emerged as the most crucial and perhaps controversial sector for the assessment of climate change impacts on the market economy in the U.S.

Besides differences in assumptions, the differences in agricultural impact estimates reflect differences in economic methodology which are of some general interest. The approaches in the literature can be divided into three broad categories. One is the *agronomic* approach, based on the use of agronomic models of crop growth to simulate the effect of changed climate conditions on crop yield and input requirements. The early studies such as those by Adams (1989) and Rosenzweig and Parry (1994) focused on the analysis of a single crop and derived the estimate of economic impact directly from the agronomic production function. Subsequent studies such as those by Kaiser et al. (1993) and Adams et al. (1995) allowed for crop substitution and combined the agronomic analysis of climate change impacts on yield and input requirements with a profit maximizing optimal choice of cropping pattern using linear or non-linear programming. The analysis, however, is usually limited to a consideration of variable but not fixed costs of production. It often turns out to be necessary to add some artificial constraints in order to make the programming model solution replicate actual farmer behavior in the baseline period. Moreover, the analysis is focused on the agricultural sector alone and it ignores the linkages with the remainder of the economy which would render the input prices and input allocations to agriculture more truly endogenous.

This is remedied in the *computable general equilibrium* (CGE) approach, which models agriculture in relation to the other major sectors of the economy and allows resources to move between sectors in response to economic incentives. An example is the Darwin et al. (1995) eight-region CGE model of the world agricultural economy. However, while a CGE model has the advantages of making prices endogenous and accounting for inter-sectoral linkages, this comes at the cost of quite drastic aggregation whereby spatially and economically diverse sectors are characterized through a representative farm or firm.

In summary, on the one hand the agronomic models do not fully capture the adaptation and mitigation strategies of farmers in the face of climate change, while on the other hand the CGE models are only applied for highly aggregated sectors of the economy. Mendelsohn, Nordhaus and Shaw (1994), hereafter MNS, provide an interesting middle ground. MNS propose what they call a *Ricardian* approach, based on the notion that the value of a tract of land will equal the discounted value all future rents that can be derived from the land. If the price were lower, rational speculators would buy up the land because the entitlement to the discounted future rents exceeds their cost. If the price were higher, a rational farmer would immediately sell the land and use the proceeds to obtain a larger annuity. MNS use the existing cross-sectional variation in temperature and precipitation among the different counties of the U.S. to estimate a reduced-form *hedonic farmland value function* that provides a direct relationship between farmland value and climate variables. The estimated hedonic equation therefore incorporates the actual response of farmers to differing climatic conditions, instead of the hypothetical responses modeled by the programming models. Moreover, it accounts for all of the production costs that affect farm profit. Adams et al. (1998) acknowledge that "the strength of [the hedonic approach] is that structural changes and farm responses are implicit in the analysis; freeing the analyst from the burden of estimating the effects of climate change on particular region-specific crops and farmer responses." Further, the hedonic function also allows one to calculate the direct impact on each farmer, county or state, in contrast to the highly aggregated structural CGE models.

MNS have received considerable attention not only because they employ a different methodological approach but also because they reach a conclusion that differs quite substantially from other results in the literature. They evaluate the impact of a climate change associated with the benchmark doubling of atmospheric concentrations of greenhouse gasses, consisting of a five degree Fahrenheit increase in temperate and an eight percent increase in precipitation (IPCC (1990); NAS (1992)). Their preferred model implies that this change will benefit U.S. agriculture overall, increasing aggregate farmland profitability by almost $2 billion per year. Based on this result, MNS comment that "whereas past production-function studies focus ominously on the vulnerable cool-weather grains, the comprehensive crop-revenue Ricardian model reminds us that the irrigated warm-weather crops may be a silver lining behind the climate-change cloud."[3]

Their findings have generated some debate in the literature, including exchanges between Cline (1996), Quiggin and Horowitz (1999), and Darwin (1999), and Mendelsohn and Nordhaus (1996, 1999a, 1999b). An issue raised by Cline and Darwin is the implications of irrigation for their analysis of climate change impacts. Cline argues that the MNS approach "implicitly assumes infinitely elastic supply of irrigation water at today's prices." Darwin argues that the MNS hedonic regression fails to control for irrigation and this may bias the regression coefficients. Mendelsohn and Nordhaus (1999b) respond to Darwin's criticism by estimating a new two-equation model; one equation is a regression of the percent of farmland irrigated in a county on climatic and other variables, and the second equation is the original MNS regression of farmland value per acre on climatic and other variables modified by an additional regressor, the predicted percent of farmland irrigated in the county derived from the first equation. This is equivalent to assuming that irrigation affects the constant term in the hedonic regression equation *but not the slope coefficients*. When MNS introduce irrigation into the hedonic regression in this way, the effect is to raise, not lower, the beneficial impact of climate change on U.S. agriculture. Subsequent studies by Mendelsohn et al. (1996) and Mendelsohn and Neumann (1999) elaborating on the MNS model, show an even larger positive economic benefit to U.S. agriculture from global climate change.

In this paper we revisit the question of how irrigation affects the estimation of climate change impacts on agriculture, both conceptually and empirically. At the conceptual level, we show that the MNS analysis makes some implicit assumptions about irrigation that are questionable. It assumes that the water supply depends on current precipitation and temperature in the growing area, which is true for dryland farming areas but is generally false for irrigated areas, and it assumes that the full cost of irrigation water supply is capitalized in farmland values, which is likely to be true in dryland areas and perhaps in irrigated areas supplied by local groundwater but not in irrigated areas supplied by surface water (which account for 63% of the total irrigation use in the U.S.). The implication is that we expect the entire hedonic regression, not just the constant term, to be different for dryland versus irrigated areas. Accordingly, we reanalyze the MNS data, along with new data on applied irrigation water from USGS and more recent data on farmland values, to determine the extent to which their results reflect their particular implementation of the Ricardian approach. We find that dryland and irrigated counties do *not* have the same slope coefficients and therefore cannot be pooled in a single regression, even with separate constant terms based on irrigation. A feature of the MNS results, noted by Kaufmann (1998) and Darwin (1999), is that these are highly sensitive to how they weight the data. We show that this sensitivity is largely associated with the irrigated counties and is an artifact of their combining irrigated and dryland counties in a single regression equation; it disappears when the dryland counties are analyzed separately. Moreover, when the dryland counties are analyzed separately, the implication of this hedonic analysis is that climate change will have a substantial *adverse* economic impact on farming in those counties.[4]

The paper is organized as follows. Section 2 explains the conceptual issues raised by irrigation for the Ricardian approach to climate change impact assessment. Section 3 discusses the econometric issues associated with weighting; it shows why the weights preferred by MNS are statistically inappropriate and are likely to produce biased coefficients, and it proposes alternative weights that account for the spatial correlation as well as the heteroscedasticty that is present in the MNS regressions. Section 4 presents our own econometric analysis of the Ricardian model which is used in Section 5 to determine the impacts of climate change on U.S. agriculture. Section 6 summarizes our conclusions.

## 2 Why Irrigation Makes a Difference

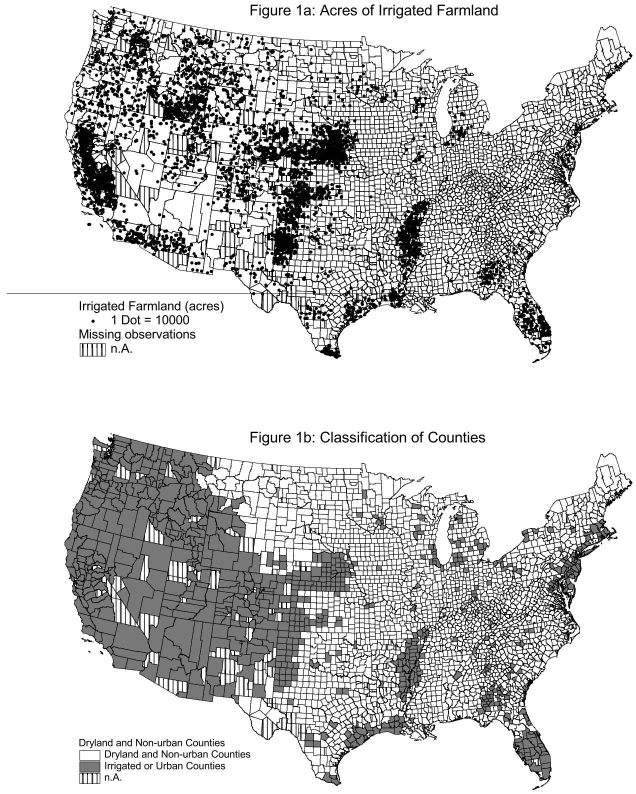
Climate general circulation models (GCMs) generate predictions of regional average annual or monthly precipitation and temperature. To assess the impact on the agricultural economy of a change in precipitation, researchers usually treat this as equivalent to a direct change in crop water supply. Water is used up in plant growth through evaporation from the soil surface and through transpiration by the plant, together known as evapotranspiration (ET). Crop yield is generally taken to be a function of ET, with a minimum threshold level of ET below which no yield is obtained; beyond the minimum, crop yield is often a linear function of ET up to some maximum level (Vaux and Pruitt 1983). With dryland farming, plant ET is met by (1) precipitation falling on the field after planting and (2) water available in the root zone of the soil at the time of planting (which, in turn, is a function of soil characteristics and precipitation in the period preceding planting). For example, corn in Iowa has an ET of about 22 inches, of which about 2 inches is likely to be supplied by available soil moisture at planting at the end of April or early May, and the rest by precipitation between May and August (Al-Kaisi 2000). With dryland farming, consequently, a change in field-level precipitation affects the plant's ability to meet ET and, through this, crop yield.

With irrigated farming, water from another source is used to supplement field-level precipitation. This destroys the link between current precipitation in a growing area and crop yield. In California's San Joaquin Valley, for example, the major crop is cotton and the ET for cotton in that area is about 31.5 inches. Without irrigation, the available soil moisture in the San Joaquin Valley at the time of planting in April is less than 1 inch, and the effective precipitation during the growing season of May through September is also less than 1 inch. Together, less than two inches of the 31.5 inches of crop ET can be supplied by local rainfall; about 30 inches (95%) has to be supplied by irrigation water obtained from local groundwater or from surface water diverted from a distant river and conveyed to the farming area (California Department of Water Resources 1986).[5] In the case of groundwater irrigation, the crop water supply depends on precipitation during the geologic past either in the growing area or in some other area that recharges the local aquifer. In the case of surface water irrigation, it depends on rainfall or snowmelt in a river basin catchment area which becomes streamflow and is then impounded, stored, and subsequently conveyed to the farming area. With irrigation from surface water, therefore, water supply depends on precipitation in areas other than the growing area, and it depends not just on current precipitation but rather on previous years' precipitation that has been impounded and stored. This, in turn, depends on the physical capacity of reservoirs and canals and their operating rules, as well as on surface evaporation and leakage. Consequently, the effect of climate change on the agricultural economy in an irrigated area depends hardly at all on local precipitation during the growing season; instead it is mediated through the functioning of a water storage and conveyance system.

That irrigation is employed as a substitute for deficient local precipitation can be seen by comparing irrigation versus average July precipitation across U.S. counties.[6] Average July precipitation in the counties where less than 5% of the of the farmland area is irrigated is 3.23 inches (these counties are displayed in Figure 1); average July precipitation in counties where 5% or more of the farmland is irrigated is 1.95 inches, a significant difference.[7] [8] This conclusion is confirmed by estimating a probit model of the percentage of farmland irrigated in a county on climate and other variables for that county.[9] The coefficients, shown in Appendix Table 7, indicate that April and July temperatures are highly significant determinants of the proportion of farmland under irrigation.

Not only does irrigation break the hydrological link between local precipitation and crop yield, but it also has some important economic implications for the assessment of climate change impacts, particularly in the case of surface water irrigation.[10] The storage and conveyance of surface water for irrigation is extremely capital intensive and the capital is very long-lived. The effective life of dams and canals in many cases is 50-100 years, and the capital costs of a reservoir can account for over 80% of the total annual cost (California Department

Figure 1: Irrigated Counties in Data Set




of Water Resources 1998). Because of the fixity of capital, the economics of water storage and conveyance systems are sensitive not only to changes in total annual precipitation but also to changes in the distribution of precipitation within the year, assuming the system is capacity-constrained (as it true of many of those in the western states). In California, for example, during the next century the summers will become warmer, and the winters will become warmer and wetter. In consequence, more of California's precipitation is likely to fall as rain and less as snow, a change that is likely to lead to increased winter runoff and reduced summer streamflow.[11] Lettenmaier and Sheer (1991) conclude that, even under climate scenarios involving an increase in total annual runoff, it will not be possible to retain the increased winter runoff with California's existing reservoir system and there will be a decreased water supply during the summer. The result is a reduction in the effective annual total supply of stored surface water, unless new storage capacity can be added to the system.

This is a distinctly different consequence than would occur with a similar pattern of climate change in a dryland farming region. With irrigated agriculture, the costs imposed by climate change can take the form of increased expenditures on surface water supply facilities instead of, or as well as, reduced crop yield.

Although the costs associated with reduced crop yield are likely to be captured in a hedonic regression, those associated with changes in surface water supply for irrigated areas are not. Since the U.S. Bureau of Reclamation (BOR) subsidizes the water it supplies for irrigation, the full cost of this water supply is not likely to be capitalized in farmland prices within the Bureau's service areas and therefore this cost will not be adequately reflected in a hedonic equation estimated with farmland prices from those areas. The BOR subsidy comes about in several ways. When a water supply project is built, the construction costs allocated to irrigation, municipal and industrial water supply, and hydroelectric power generation are reimbursable by the beneficiaries, but no reimbursement is sought for costs allocated to purposes such as navigation, flood control, and recreation. Critics have argued that the cost allocation is manipulated to reduce both the overall reimbursable component of costs and the portion allocated to irrigation. While the Bureau requires municipal and industrial users and power purchasers to pay interest on their share of construction costs from the start of construction through the completion of repayment, it charges no interest at all to irrigators. Since BOR projects can take a couple of decades or more for construction to be completed and the repayment period is usually 40 or 50 years from the date of completion, waiving interest is a massive subsidy to irrigation. But, this is not the only subsidy. If the charge for irrigation water is deemed to exceed the irrigators' ability to pay, their payment is reduced accordingly. Moreover, in particular cases, Congress has granted additional relief to irrigators for part or all of their cost allocation. The consequence is as follows. Between 1902 and 1994, the federal government spent $21.8 billion to construct 133 water supply projects in the western United State that provide water for various purposes including irrigation.[12] Although most of the water supplied by these projects goes to irrigation, the cost allocated to irrigation amounted to \$7.1 billion (33%). Of this, \$3.7 billion was subsequently waived. Of the remaining \$3.4 billion payable by irrigators, only \$0.95 billion had actually been repaid as of September 30, 1994 (General Accounting Office 1996). The remaining balance will not be paid off until well into this century. The combined effect of these subsidies is that recipients of irrigation water from federal water projects pay, on average, about 10 cents on the dollar for the construction cost to supply this water.[13]

The pricing of BOR irrigation water has two implications for the hedonic analysis of the effects of climate change. First, there is substantial variation in the BOR irrigation charges across different projects, reflecting differences in the date of construction, the length of repayment period, whether or not repayment has been waived, etc. If BOR subsidies are capitalized in farmland values as Huffaker and Gardner (1986) and others have concluded, it would seem desirable to include water price as a variable in a hedonic regression covering irrigated areas served by BOR in order to control for the price variation; the failure to do so could bias the other regression coefficients. Second, because of the BOR subsidies, the change in farmland values predicted to follow from a change in precipitation by a hedonic regression based on irrigated areas served by BOR would fail to reflect most of the capital cost of irrigation supply. While this cost is not currently borne by the recipients of BOR irrigation water, it is a real economic cost that needs to be accounted for in any assessment of climate change impacts.

However, while the BOR subsidy for irrigation represents an important price distortion, its overall significance should not be overstated. In the western states that it serves, the Bureau's water accounts for only about 19% of the total irrigation supply. The remainder of the irrigation supply in these states comes from groundwater or from non-federal surface water storage projects. Neither of those sources of water is subsidized to any significant degree. Nevertheless, in the case of irrigation with non-federally supplied surface water it still can be misleading to predict the economic cost of a change in precipitation on the basis of a hedonic regression of current farmland values. This is because, although non-federal surface water is generally not subsidized, it is still priced at a level far below the current replacement cost. The general practice of water districts in the western states is to charge farmers for irrigation water so as to recover current O&M costs plus historical construction costs, albeit with interest (Gardner et al. 1982).[14] Because surface water storage and conveyance construction costs have increased substantially over time, and because this capital is long-lived, historical construction cost is generally far below current replacement cost.[15] By way of illustration, the California State Water Project (SWP), constructed between 1961 and 1973, supplies (unsubsidized) water to irrigation districts in Kern County at a wholesale cost of about $70/AF. But, the SWP has only about 60% of the supply capacity that was originally planned in 1960 - completion of the remainder has been blocked since 1982, when voters rejected Proposition 9 to build the Peripheral Canal. If the system were now to be built out, current estimates are that the new water storage facilities would cost on the order of $500-1,000/AF (California Department of Water Resources 1998, Frederick and Schwarz 2000). The price that farmers in Kern County pay for SWP water reflects what it cost to construct the SWP in the 1960s, not what it would cost to complete the SWP now; it is the historical cost that is capitalized in current land values there, not the future cost of expansion. Hence, the change in farmland values predicted from a hedonic regression involving areas served by the SWP, or other non-federal projects, would probably not account for the full cost of the new surface water supply capacity that might be needed in the event of a reduction in annual runoff due to climate change. The extra capital cost would need to be factored into the assessment separately.[16]

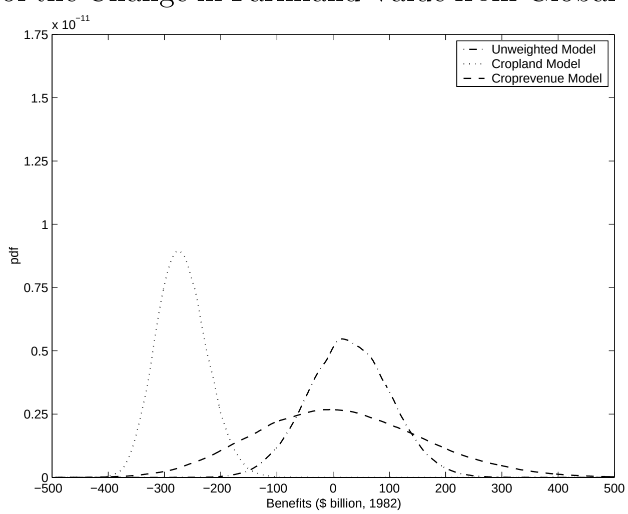
Thus, for both hydrological and economic reasons, we believe that the economic effects of climate change on agriculture need to be assessed differently in dryland and irrigated areas. In dryland areas, climate change is equivalent to an exogenous shift in the fixed supply of an unpriced input. In irrigated areas, local climate is not directly connected to water supply; moreover, if there is a reduction in water supply, there would be a substantial price increase associated with any new supply compared to that of the existing supply because of escalation in reservoir construction costs and the tendency to price existing surface water supplies on the basis of historical cost.[17] Estimating the economic impact of climate change on U.S. agriculture on the basis of a single hedonic model fitted to a data set that combines both dryland and irrigated farming areas is thus likely to be questionable on econometric grounds, since it combines what we expect to be two heterogeneous equations in a single regression, as well as on economic grounds, since we expect it to understate potential capital costs in areas needing increased surface water irrigation.

# 3 The Role of Weighting

In using a hedonic regression to measure the effect of a change in climate on farmland value one is seeking to estimate what statisticians call a treatment effect (Moffitt 1999). The ideal way to measure this effect would be to run a controlled experiment, assigning counties at random to alternative climate conditions independently of all county characteristics (input prices, urbanization, soil characteristics, etc) and then measuring the resultant change in farmland values. Since this is impractical, one uses instead observational data on climate and farmland value in what Mendelsohn et al. (1996) characterize as a "natural experiment." In place of random assignment of climatic conditions, one attempts to control for non-climate county characteristics by including covariates. However, this may be an imperfect solution. Observational data are vulnerable to selection bias, missing variables, measurement error, and function mis-specification; therefore, the analysis needs to be conducted with some caution.[18]

A statistical issue that turns out to play a crucial role in the hedonic analysis is weighting of the data. As noted earlier, MNS use two alternative weights: *cropland*, whereby the observations are weighted by the percentage of each county in cropland[19], and *crop revenue*, whereby the observations are weighted by the aggregate value of crop revenue in each county. The two weights produce different coefficient estimates and different estimates of the economic impact of climate change on U.S. agriculture. Table 1 presents the MNS estimate of the change in aggregate U.S. farmland value associated with a climate change scenario consisting of a five degree Fahrenheit uniform increase in temperature and an eight percent increase in precipitation, using each set of weights.[20] For comparison, in the last row we also show estimates obtained by repeating the MNS regression with no weighting of the observations. Depending upon whether one weights and how one weights, U.S. agriculture could gain or lose from climate change. The estimate preferred by MNS is that associated with crop revenue weights, a net gain to U.S. agriculture of $21.3 billion in farmland value.[21] It is also instructive to examine the uncertainty inherent in these estimates. We used the bootstrap method to develop a probability distribution of regression coefficient estimates, from which we derived a probability distribution of aggregate impact on U.S. farmland value for each of the three weighting schemes.[22] The smoothed, distributions of farmland value impact are

Figure 2: Distribution of the Change in Farmland Value from Global Warming, All Counties.




shown in Figure 2 and the 95% confidence intervals are summarized in the second column of Table 1[23]. The results show that the crop revenue weights yield the least precise estimate of climate change impact, ranging from a possible loss of $256.7 billion to a possible gain of $320.5 billion. With such a wide confidence interval, a point-estimate can be somewhat misleading.

Table 1: Change in Farmland Value from Global Warming, using All U.S. Counties in the Estimation. Damages Evaluated for Subsets of Counties Described in Figure 1 ($ billion, 1982)

| Model | Point Estimate | 95% Confidence Interval |
|---|---|---|
| **Cropland Weights** | | |
| Dryland, Non-urban Counties | -175.6 | (-227.3 ; -111.9) |
| Irrigated and Urban Counties | -97.4 | (-124.3 ; -63.7) |
| All Counties Combined | -273.0 | (-350.5 ; -177.0) |
| **Crop Revenue Weights** | | |
| Dryland, Non-urban Counties | 34.4 | (-162.3 ; 229.2) |
| Irrigated and Urban Counties | -13.2 | (-95.7 ; 93.4) |
| All Counties Combined | 21.3 | (-256.7 ; 320.5) |
| **No Weights** | | |
| Dryland, Non-urban Counties | 25.3 | (-67.8 ; 116.2) |
| Irrigated and Urban Counties | 6.8 | (-46.9 ; 58.7) |
| All Counties Combined | 32.2 | (-114.0 ; 172.7) |

These results focus attention on whether one should weight, and if so how. It is perhaps noteworthy that, while there have been other studies involving hedonic regressions of farmland value, many of those studies did not weight the data and those that did employed weights which were different from those used by MNS.[24] MNS motivate their cropland weights with the argument that "counties with a large fraction of cropland should provide a better reading on price determination because other influences, such as cities or forests, are minimized." We will suggest below an alternative approach to dealing with the influence of urbanization on farmland values.[25] MNS motivate their crop revenue weights with the argument that this "emphasizes those counties which are most important to total agricultural production even though some of the counties might have their land values affected by large neighboring cities; it also places greater weight on counties where more valuable crops are grown." In addition to dealing differently with urban impacts on farmland value, the approach we describe below explicitly takes account of the fact that unmeasured factors in one county may influence land values in a neighboring county. Moreover, their argument points to what could be a serious flaw in crop revenue weights. The counties with the highest crop revenue per acre in the U.S. are irrigated counties. We argued above that irrigation is likely to be an omitted variable in the MNS regression. Using crop revenue to weight the observations therefore runs the risk that the regression weights are correlated with the error term, which can induce bias in the coefficient estimates. The data support this contention: the correlation coefficient between the percentage of farmland in the county irrigated and the county crop revenue is 0.389.[26] Also, the residuals from the MNS weighted regressions show strong signs of heteroscedasticity which, as Zietz (2001) notes, can be an indication of a problem with omitted variables; in these circumstances, heteroscedasticity can cause bias not only in the standard errors but also in the estimated regression coefficients themselves.

When other researchers have employed weights in regressions of farmland value using county data, they have done so mainly for two reasons.[27] First, counties vary in size, and this affects the estimate of land value per acre. The average county in California had about 554,429 acres of farmland in 1982, while the average county in Georgia had 77,307 acres of farmland. This difference obviously affects the variances of farmland value per acre, and it can be corrected by weighting each observation by the number of farmland acres in the county.[28] More recently, researchers have paid attention to the possibility of spatial correlation across geographical areas. If there is an unusual shock to farmland value in one county because of some unmeasured locational characteristic, for example because it is close to an urban area or far from rail transportation, the chances are that the adjoining counties will also experience a shock to farmland value because they share similar locational characteristics. This can be captured by allowing for spatial correlation among the error terms in neighboring counties.[29] We now describe a model that incorporates both of these considerations in the specification of the error term for a hedonic regression.

We start with the issue of spatial correlation among counties. Suppose that the true value per acre of farmland $\bar{V}_j$ in county j is a linear function of climatic, soil, locational, and socioeconomic variables $\mathbf{Z}_j$ (these are listed in an supplementary appendix available upon request):

$$\bar{V}_j = \mathbf{Z}_j' \boldsymbol{\beta} \tag{1}$$

However, the recorded value per acre of farmland in county j is measured with error; the county-specific error is denoted $\eta_j$.

$$V_j = \bar{V}_j + \eta_j \tag{2}$$

Following the approach of Anselin (1988) and Griffith (1988), the spatial correlation of the error terms across counties can be modeled (in matrix notation) as

$$\boldsymbol{\eta} = \rho \mathbf{W} \boldsymbol{\eta} + \mathbf{u} \tag{3}$$

Here, $\mathbf{u}$ is the vector of error terms that are independently normally distributed with $\mathbb{E}[u_j] = 0$ and $VAR[u_j] = \sigma_j^2$, $\rho$ is the parameter of spatial correlation, and $\mathbf{W}$ is the spatial weighting or "contiguity" matrix which influences the form of the spatial dependence. The (i,j) element of $\mathbf{W}$ is positive if counties i and j have a common boundary, and zero otherwise. $\mathbf{W}$ is generally normalized so that the elements in each row sum to unit, which implies an equal value for the non-zero elements in each row. To weight the relative influence of each county, the non-zero elements for each pair of contiguous counties were multiplied by the inverse of the distance between the county centroids and then row-normalized.[30] The product $\mathbf{W}\boldsymbol{\eta}$ is a vector with weighted averages of errors in continguous counties, and $\rho$ indicates the correlation between a county's error and the composite of the errors of its immediate neighbors. In the standard applications of spatial correlation $\sigma_j^2 = \sigma_u^2$ for all $j$, but in our case $V_j$ is a county-wide average of the value of farmland and therefore the error terms $u_j$

are heteroscedastic and can be represented as

$$u_j = \frac{\sum_{i=1}^{N_j} A_{i,j} * \nu_{i,j}}{\sum_{i=1}^{N_j} A_{i,j}} \tag{4}$$

where $A_{i,j}$ is the acreage of the ith farm in county j and $\nu_{i,j}$ is white-noise error term associated with the value of the farmland owned by the ith farm in county j (note that the farmland value data is collected on a farm-by-farm basis). The $\upsilon_{i,j}$ are iid normal variates with $\mathbb{E}[\nu_{i,j}] = 0$ and $VAR[\nu_{i,j}] = \sigma_\nu^2$. Define the farmland shares as $s_{i,j} = \frac{A_{i,j}}{\sum_{i=1}^{N_j} A_{i,j}}$; then $VAR[u_j] = \sigma_\nu^2 \sum_{i=1}^{N_j} s_{i,j}^2$. In our case, therefore, the variance-covariance matrix of $\mathbf{u}$ is a diagonal matrix $\sigma_\nu^2\Omega$ where the elements on the diagonal of $\Omega$ are the sum of squared farmland shares. The inverse $\Omega^{-1}$ can be factored into the product of $\mathbf{P}$ and its transpose $\mathbf{P}'$ such that $\mathbf{P}'\mathbf{P} = \Omega^{-1}$. The model in equation (1) can then be transformed into a standard linear regression model with iid error terms,

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} \tag{5}$$

where

$$\mathbf{y} = (\mathbf{I} - \rho\mathbf{W})\mathbf{P}\mathbf{V} \tag{6}$$

$$\mathbf{X} = (\mathbf{I} - \rho\mathbf{W})\mathbf{P}\mathbf{Z} \tag{7}$$

$$\boldsymbol{\epsilon} = (\mathbf{I} - \rho\mathbf{W})\mathbf{P}\eta \tag{8}$$

Here, $\boldsymbol{\beta}$, $\rho$ and $\sigma_\nu^2$ are to be estimated from the data. We will refer to our weights incorporating both the spatial correlation of the error terms $\boldsymbol{\eta}$ and the heteroscedasticity of the error terms $\mathbf{u}$ as the *feasible GLS* model in order to contrast it with the MNS cropland and crop revenue models.[31] By the Gauss Markov Theorem, the feasible GLS estimate of $\boldsymbol{\beta}$ will generate an estimate of the change in farmland value $\Delta V$ induced by a change in climate, $\Delta Z$, that has a minimum mean square error.

The most difficult problem in using the feasible GLS weights is the estimation of $\rho$ and $\sigma_\nu^2$. Researchers originally approached this via maximum likelihood (ML) estimation, However, in a data set with our dimensionality, this is an exceptionally cumbersome computation. Recently, researchers have adopted Generalized Method of Moments (GMM) estimation (Kelejian and Prucha 1999). The GMM procedure relies on the following three moment conditions to estimate $\rho$ and $\sigma_\nu^2$:

$$\mathbb{E}\left[\frac{1}{N}\boldsymbol{\eta}'\mathbf{P}'(\mathbf{I}-\rho\mathbf{W})'(\mathbf{I}-\rho\mathbf{W})\mathbf{P}\boldsymbol{\eta}\right] = \sigma_\nu^2 \tag{9}$$

$$\mathbb{E}\left[\frac{1}{N}\boldsymbol{\eta}'\mathbf{P}'(\mathbf{I}-\rho\mathbf{W})'\mathbf{W}'\mathbf{W}(\mathbf{I}-\rho\mathbf{W})\mathbf{P}\boldsymbol{\eta}\right] = \frac{\sigma_\nu^2}{N}Tr(\mathbf{W'W}) \tag{10}$$

$$\mathbb{E}\left[\frac{1}{N}\boldsymbol{\eta}'\mathbf{P}'(\mathbf{I}-\rho\mathbf{W})'\mathbf{W}'(\mathbf{I}-\rho\mathbf{W})\mathbf{P}\boldsymbol{\eta}\right] = 0 \tag{11}$$

Using Monte Carlo simulations, Kelejian and Prucha show that the GMM procedure yields results that are similar to ML but requires considerably less computer time and is far more stable than the ML procedure.[32] The next section presents the results we have obtained using the feasible GLS weights and GMM estimation.

# 4 Model Estimation

We have argued that, for both hydrological and economic reasons, the economic impact of climate change on U.S. agriculture needs to be assessed differently in dryland and irrigated areas. In dryland areas, a hedonic regression relating farmland value to local climate conditions in the farming area appropriately captures the link between climate and the farm economy. In irrigated areas, however, local precipitation and temperature do not provide an accurate measure of the water supply available to farmers. Therefore, a hedonic regression is likely to be meaningless unless one uses a different set of variables to measure the available water supply. Because the water supply in irrigated areas depends on groundwater or imported surface water, the availability of water needs to be measured on a case by case basis for each farming region using specific information about the supply arrangements in that region. Unfortunately, there exists no national data base on stored water availability in irrigated areas analogous to the precipitation and temperature data available through the National Climatic Data Center. In these circumstances, we believe that the appropriate course of action is to restrict the application of the hedonic model to dryland farming areas in the U.S., thereby providing a partial rather than a complete national assessment of the economic impact of climate change on U.S. agriculture.

In their discussion of weights, MNS emphasize the importance of insulating the farmland value regression equation from the influence of cities. There can be farmland acreage in counties that are almost entirely urban, such as Nassau County on Long Island in New York.[33] Farmland in these urban counties has an inflated value compared to farmland elsewhere because of the option value of the land for urban development (and also, perhaps, because of superior access to urban consumers). Plantinga et al. (2002) examine the effects of potential land development on farmland prices and find that a large share of farmland values, e.g., 82% in New Jersey, is attributable to the option value to develop the land for urban uses. MNS propose to insulate their hedonic regression from these unusual urban effects by using cropland or crop revenue weights. We prefer instead to drop these counties from the regression analysis because the land value equation that applies to these counties is likely to have a different specification from that in normal farming counties.[34] Ideally one would analyze these urban counties in a separate regression but, as with the irrigated counties, the present data set does not contain the variables necessary to characterize the determination of farmland values in those counties.

Of the 2938 counties in the MNS data, 525 are irrigated (i.e., more than 5% of their farmland acreage is irrigated), and 156 are urban (i.e, they have a residential density of more than 400 people per square mile;[35] in addition, 32 counties are both urban and have irrigated farming. Accordingly we will omit these counties from the estimation of the farmland value regression equation, leaving a sample of 2186 dryland, non-urban counties.[36]

With regard to weighting, we have argued that the nature of the dependent variable - the average value per acre of farmland in each county - calls for a feasible GLS model which allows for both spatial correlation and heteroscedasticity in the error term of the hedonic regression. In this section, we report the results of estimating the hedonic regression model for the 2186 dryland, non-urban counties using the feasible GLS weights. We then compare these results to those obtained using feasible GLS weights, as well as the MNS weights, applied to the full set of 2938 counties.

We use the same variables as MNS.[37] The feasible GLS weights are based on the sum of squared farm acreage shares for each county, $\sum_i s_{i,j}^2$. Due to privacy restrictions, the Census does not provide data on farm acreage shares in each county, but it does provide data on the size distribution of farms in each county from which we were able to approximate these shares. The details of this calculation are described in Appendix 2.

The regression coefficients obtained using the feasible GLS weights are shown in the first column of Table 2; the other columns show the coefficients associated with cropland weights, crop revenue weights, or no weights. Several features of these results should be noted. First, the signs of some of the coefficients in Table 2 make better sense agronomically than the MNS coefficients, especially July precipitation and slope length. It was noted earlier that crop ET is greater in July than in any other month. Therefore, one would expect that, ceteris paribus, having more precipitation in July is beneficial to farmland value. However, the MNS regressions regression results imply otherwise: at current precipitation levels, their results imply that an increase in July precipitation lowers farmland value.[38] A possible explanation for this counterintuitive result is their failure to control adequately for irrigation. The most valuable farmland in the U.S. is found in California, where there is almost no precipitation in July; this land is valuable despite, not because of, the absence of summer precipitation. In Table 2 where we restrict the hedonic regression to dryland, non-urban counties, the anomaly disappears and farmland value is increasing in July precipitation at the current mean precipitation level. Similarly, one would expect farmland value to be lower on land

Table 2: Regression Results Using Only Dryland, Non-urban Counties

| Variable | FGLS | Cropland | Crop Revenue | Unweighted |
|---|---|---|---|---|
| Constant | 1312 | 1385 | 1431 | 1287 |
| | (44.41) | (44.25) | (45.14) | (48.96) |
| January temperature | -75.4 | -74.0 | -89.4 | -51.4 |
| | ( 7.15) | ( 6.88) | ( 8.23) | ( 5.84) |
| January temperature squared | -0.463 | -0.733 | -1.42 | -0.59 |
| | ( 1.87) | ( 3.10) | ( 6.13) | ( 2.95) |
| April temperature | -17.3 | -12.3 | 27.6 | -8.24 |
| | ( 1.09) | ( 0.83) | ( 1.86) | ( 0.62) |
| April temperature squared | -1.41 | -2.98 | -1.50 | -0.480 |
| | ( 1.90) | ( 3.57) | ( 2.07) | ( 0.84) |
| July temperature | -153 | -174 | -166 | -141 |
| | (10.79) | (11.23) | (10.81) | (11.33) |
| July temperature squared | -4.07 | -4.77 | -5.34 | -5.20 |
| | ( 4.27) | ( 5.13) | ( 5.45) | ( 6.96) |
| October temperature | 171 | 184 | 152 | 164 |
| | ( 8.91) | ( 8.57) | ( 7.13) | ( 9.02) |
| October temperature squared | -6.63e-02 | 2.43 | 2.17 | 0.468 |
| | ( 0.06) | ( 2.09) | ( 1.92) | ( 0.52) |
| January precipitation | -34.2 | -24.0 | -4.54 | -23.2 |
| | ( 1.39) | ( 0.90) | ( 0.16) | ( 0.98) |
| January precipitation squared | -8.31 | -8.89 | -8.41 | 2.72 |
| | ( 1.10) | ( 1.18) | ( 1.05) | ( 0.42) |
| April precipitation | 89.7 | 88.0 | 25.5 | 93.4 |
| | ( 3.25) | ( 3.58) | ( 1.01) | ( 4.78) |
| April precipitation squared | -12.2 | 7.25 | 19.2 | -5.79 |
| | ( 0.99) | ( 0.65) | ( 1.64) | ( 0.69) |
| July precipitation | 37.0 | 20.6 | 64.4 | 32.3 |
| | ( 2.04) | ( 1.15) | ( 3.50) | ( 2.13) |
| July precipitation squared | 21.2 | 22.6 | 21.3 | 9.15 |
| | ( 2.51) | ( 3.05) | ( 3.17) | ( 1.78) |
| October precipitation | -81.5 | -125 | -76.2 | 15.0 |
| | ( 2.88) | ( 4.54) | ( 2.67) | ( 0.60) |
| October precipitation squared | -3.21 | -28.2 | -62.6 | 8.25 |
| | ( 0.14) | ( 1.10) | ( 2.42) | ( 0.41) |
| Per capita income | 7.92e-02 | 9.28e-02 | 8.89e-02 | 7.90e-02 |
| | (17.31) | (18.94) | (16.76) | (16.57) |
| Population density | 1.55 | 1.80 | 1.56 | 2.02 |
| | (13.03) | (12.19) | (10.81) | (14.33) |
| Population density squared | -2.45e-03 | -4.63e-03 | -3.31e-03 | -3.60e-03 |
| | ( 3.45) | ( 4.65) | ( 3.79) | ( 3.94) |
| Latitude | -127 | -111 | -99.3 | -39.7 |
| | ( 6.89) | ( 5.58) | ( 5.13) | ( 2.56) |
| Altitude | -0.163 | -0.252 | -0.246 | -0.127 |
| | ( 4.92) | ( 6.40) | ( 6.12) | ( 4.06) |
| Soil salinity | -143 | -614 | -6.51 | -304 |
| | ( 0.61) | ( 2.61) | ( 0.03) | ( 1.61) |
| Flood prone | -209 | -248 | -282 | -161 |
| | ( 5.17) | ( 5.21) | ( 5.21) | ( 4.37) |
| Wetland | -203 | -147 | -343 | -35.5 |
| | ( 1.88) | ( 1.27) | ( 3.06) | ( 0.38) |
| K factor | -861 | -1403 | -1854 | -415 |
| | ( 4.78) | ( 6.87) | ( 8.65) | ( 2.36) |
| Slope length | -1.19 | -22.3 | -30.9 | -6.14 |
| | ( 0.19) | ( 3.26) | ( 4.50) | ( 0.83) |
| Sand | -17.7 | -166 | -98.9 | -111 |
| | ( 0.39) | ( 3.14) | ( 2.27) | ( 2.90) |
| Clay | 75.1 | 89.8 | 132 | 93.7 |
| | ( 4.05) | ( 4.55) | ( 6.63) | ( 4.28) |
| Moisture capacity | 0.257 | 0.426 | 0.352 | 0.378 |
| | ( 7.30) | (10.28) | (10.02) | ( 7.89) |
| Permeability | -2.87e-03 | -6.49e-03 | -9.67e-03 | 1.21e-03 |
| | ( 1.01) | ( 1.92) | ( 3.36) | ( 0.35) |

that is more prone to the loss of fertile top soil. The MNS regression includes two of the variables that enter the universal soil loss equation: soil erodibility (measured by a variable called the K-factor) and slope length (a measure of distance to the nearest river).[39] Since soil loss is increasing in both these variables, one would expect farmland value to be *decreasing* in them. However, in the MNS regressions, farmland value is increasing in slope length. Again, we suspect this is an artifact resulting from their pooling of irrigated and dryland counties in a single regression. Arid areas in the west and southwest are characterized by few natural waterways and, therefore, a greater distance to the nearest river. These areas also have some of the most valuable farmland - but this is despite, not because of, the absence of rivers. In Table 2 where we restrict the hedonic regression to dryland, non-urban counties, the anomaly disappears and farmland value is decreasing in slope length.

Second, further evidence that dryland counties should not be pooled with irrigated counties comes from a Chow test to examine whether the coefficients in Table 2 for the subset of 2186 dryland, non-urban counties are significantly different from the regression coefficients for 752 other counties included by MNS in their regressions. The $F(31, 2876)$ statistic using the feasible GLS weights is 27.6, leading to rejection of the hypothesis that the subsets have identical regression coefficients. Mendelsohn and Nordhaus (1999a) counter earlier criticisms of their treatment of irrigation by including the predicted percent of farmland irrigated in the county, derived from an auxiliary regression, as an additional right-hand-side variable in the hedonic farmland value regression. This is equivalent to allowing the percent of farmland irrigated to shift the constant term in the hedonic regression, while leaving the slope coefficients unchanged. In our view, however, this does not go far enough; for the reasons presented in Section 2, we believe that irrigation is likely to change not only the constant term but also the slope coefficients in the farmland value regression. To test this, we estimated a regression for the full set of 2938 counties allowing the constant term to vary according to the predicted percent of farmland irrigated and then performed Chow tests of the hypotheses that the slope coefficients on the climatic variables are different for the dryland and non-urban counties versus the irrigated counties (i) using the original MNS model and (ii) including the predicted irrigation percentage from Table 7 which will shift the intercept. Both hypotheses were rejected; using the feasible GLS weights, the F(16,2876) statistic for the first hypothesis is 27.1, and the F(16,2876) under the second hypothesis is 26.8.[40] We also tested each coefficient individually to see whether it is different for dryland versus irrigated counties. We found that the climatic variables, the water-related variables (slope length, flood prone, wetland, salinity and clay), population density, and income per capita, are all significantly different at the 95% level. These test results clearly demonstrate that pooling dryland and irrigated counties is not valid and will result in a misspecification.

Third, the assumptions underlying the feasible GLS weights are supported by several tests based on the residuals from an OLS regression under the null hypothesis of spatial independence. One test is the Moran-I statistic (Anselin 1988). However, since this does not have a clear alternative hypothesis, we supplemented it with two Lagrange-Multiplier tests involving an alternative of spatial dependence, the LM-ERR test of Burridge (1980) and LM-EL test of Anselin et al. (1996).[41] The results are shown in the first three rows of Table 3. We find strong statistical evidence that spatial correlation is indeed present[42] for both the entire set of counties and the subsample of dryland, non-urban counties. In each case, the data were premultiplied with the squared farmland shares in order to account for the heteroscedasticity of the county error terms.[43] Given the strong evidence of spatial

Table 3: Test for Spatial Correlation

| **Model** | **Using all counties** | **Dryland, Non-urban Counties (Figure 1 on page 8)** |
|---|---|---|
| **Tests** | | |
| Moran-I $N(0,1)$ | 43.5 | 40.9 |
| LM-ERR $\chi^2(1)$ | 1794 | 1562 |
| LM-EL $\chi^2(1)$ | 979 | 735 |
| **Parameter** | | |
| $\rho$ | 0.447 | 0.438 |

correlation, $\rho$ was calculated using the GMM estimator of Kelejian and Prucha (1999) and is listed in the last row of Table 3. The value of $\rho$ is quite high: in the dyland, non-urban subsample the error term in county j is equal to the innovation $u_j$ plus 43.8% of the weighted average of the error terms in all adjacent counties. The estimate of $\rho$ is larger for the full sample than for the dryland, non-urban subsample, reflecting the fact that irrigated and urban counties tend to be highly clustered. Hence, a hedonic regression applied to the full sample leads to error terms that are both larger and more highly spatially autocorrelated than if one removes the irrigated and urban counties.

Furthermore, regression of the residuals after correcting for spatial correlation shows that the proposed squared farmland shares perform best at explaining the heteroscedasticity of the error terms. The squared error terms were regressed on a constant term plus the inverse of each of the weights in order to determine which set of weights best accounts for the heteroscedasticity of the error terms $\mathbf{u}$. The results are presented in Table 4. We first premultiplied the data by $(\mathbf{I} - \widehat{\rho}\mathbf{W})$[44] to get a consistent estimate of the error terms $\mathbf{u}$. Irrigated counties occur predominantly in the western states where counties tend to be larger, and hence a higher variance due to the inadequate treatment of irrigation might be confounded with a lower variance due to a larger county area. The regression in Table 4 therefore only utilizes dryland, non-urban counties in the estimation to avoid such confounding. The regression results further validate our proposed weighting structure as the squared farmland shares are the only weights which significantly explain the heteroscedasticity.[45] In sharp contrast, the crop revenue weights place the greatest weight on counties with the *largest*

Table 4: Regression of Squared Error Terms on a Constant and the Inverse of the Weighting Variables for 1982

| **Model** | **Constant** | **t-value** | **Inverse of Weights** | **t-value** |
|---|---|---|---|---|
| **Crop Revenue Weights** | 57,583 | (19.98) | -39 | (0.90) |
| **Cropland Weights** | 57,262 | (20.21) | 75 | (0.65) |
| **Farmland Shares** | 52,569 | (17.40) | 1979 | (4.28) |

variance, a procedure that will result in an inefficient and imprecise estimator.

Finally, a Bayesian analysis of the residuals associated with the feasible GLS regression in Table 2 also suggests that this is performing well (Zellner (1975) and Chaloner and Brant (1988)). There are now only 10 outliers out of the 2186 observations, and there is no particular pattern to them as there is with the residuals from the hedonic regression for the full sample of 2938 counties.

# 5 Climate Change Impacts

We now turn to estimating the impact of global warming on farmland value using the regression coefficients in Table 2. The regression coefficients are estimated from the subsample of dryland, non-urban counties, and the change in aggregate farmland value is predicted for this same subset of counties using the $2XCO_2$ scenario of a five degree increase in temperature and an eight percent increase in precipitation. Point estimates of the change in farmland value and 95% confidence intervals based on bootstrapping for each of the different weighting schemes are given in Table 5. The corresponding probability distributions of impact on farmland value in the dryland, non-urban counties are shown in the upper left panel in Figure 3. There are several striking features of these results. Restricting the analysis to the subsample of 2186 dryland, non-urban counties produces relatively tight distributions of the change in farmland values compared to the very diffuse distributions resulting from the MNS coefficient estimates, which are shown in the lower left panel.[46] Moreover, the different weighting schemes now lead to very similar results with respect to both the point-estimates and the confidence intervals, shown in the upper left panel, unlike those based on coefficient estimates from the full sample of counties, shown in the lower left panel, which are extremely heterogeneous.[47] The diffuseness of the MNS estimates of climate change impact, and their sensitivity to the choice of weighting scheme, are attributable primarily to the observations on the 752 irrigated and urban counties included in the MNS regressions. This is shown by the results of fitting a hedonic farmland regression to the 752 counties and then predicting the impact of global warming on aggregate farmland value in those counties; the regressions and predictions of climate change impact are far more diffuse and heterogeneous than the corresponding results for dryland, non-urban counties.[48] The imprecision of the hedonic regression for irrigated and urban counties is consistent with our argument that the hedonic regression equation for those counties is misspecified because local climate plays a different and far smaller role in the determination of farmland values than in dryland, non-urban counties.

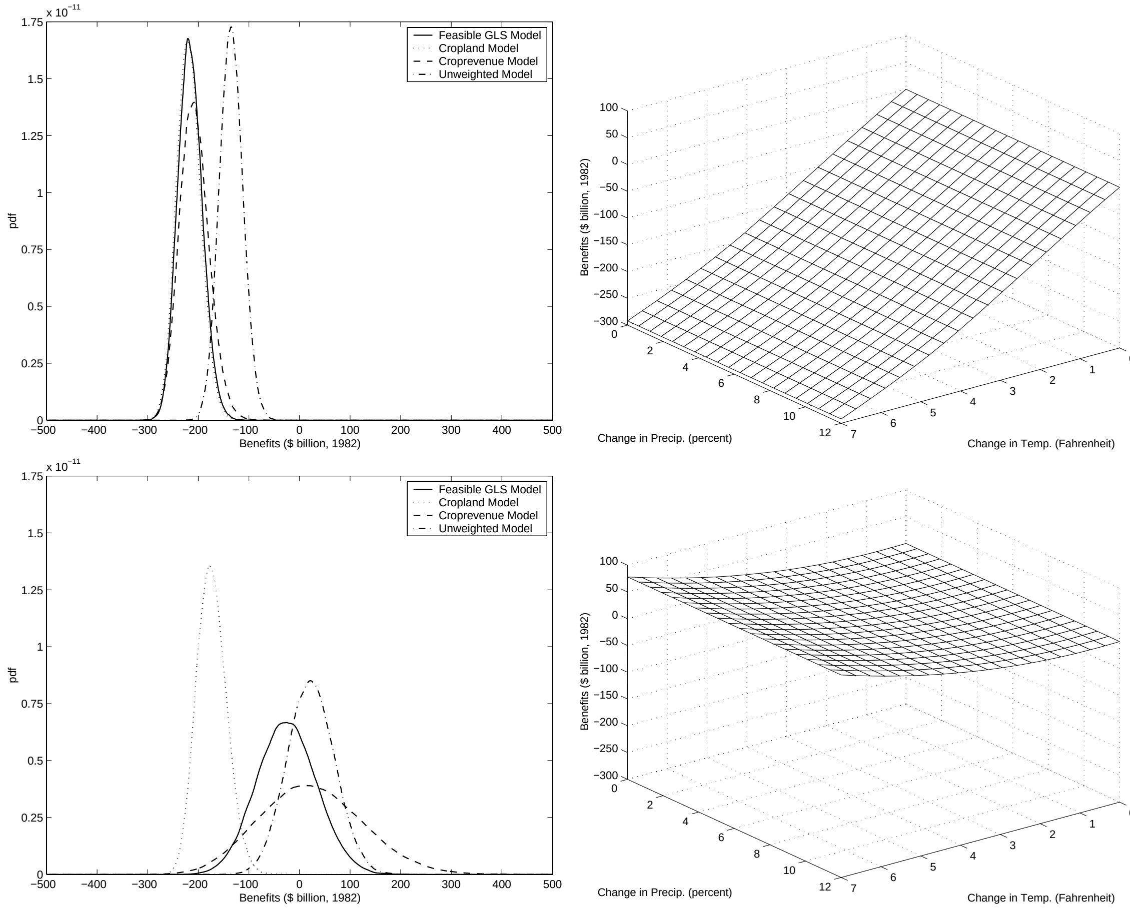
In the upper left panel in Figure 3, the distributions for the feasible GLS and cropland weights virtually lie on top of one another, and the distribution for the crop revenue weights is quite similar to them. The consensus finding is that global warming will have an adverse effect on the farm sector in the dryland, non-irrigated counties, with a point-estimate of the reduction in aggregate farmland value in these counties amounting to $208-219 billion, in 1982 prices. This would represent a roughly 40% reduction in the value of these farmland assets. Converted into annual basis[49], the implied aggregate loss in farmland profitability in dryland, non-urban counties amounts to about $6 billion per year, in 1982 dollars; converted to 1990 dollars for comparability with other estimates in the literature, this comes to about $7.9 billion.[50]

Since any single climate change scenario is likely to be unduly precise, it is also informative to consider the farmland value response surface for a range of climate change scenarios, and to compare our results for dryland, non-urban counties with the MNS results for all counties

Table 5: Change in Farmland Value in Dryland, Non-urban Counties from Global Warming, Using Only Dryland, Non-urban Counties in the Estimation ($ billion, 1982)

| **Model** | **Point Estimate** | **95% Confidence Interval** |
|---|---|---|
| **Feasible GLS Model** | -217.1 | (-260.5 ; -166.0) |
| **Cropland Weights** | -219.1 | (-263.2 ; -169.0) |
| **Crop Revenue Weights** | -207.9 | (-260.1 ; -147.7) |
| **No Weights** | -134.5 | (-179.2 ; -88.4) |

Figure 3: Change in Farmland Value from Global Warming. Impacts are Evaluated for Dryland and Non-urban Counties.




The two panels on the left depict the *distribution of climate impacts* for one climate scenario, a 5 degree Fahrenheit increase in temperature and an 8% increase in precipitation. The two panels on the right show the *point-estimate* for varying climate scenarios.
The upper two panels use only *dryland and non-urban counties* in the estimation of the hedonic coefficients, while the lower two panels use *all* observations in the estimation of the hedonic coefficients.
The upper right panel uses the feasible GLS weights, while the lower right panel uses MNS preferred crop revenue weights.

combined. The right-hand panels of Figure 3 show the point-estimate of the response of aggregate farmland value in the dryland, non-urban counties to a uniform percentage increase in year-round precipitation and a uniform increase in year-round temperature. The upper right panel is based on the feasible GLS coefficients estimated from the subset of dryland and non-urban counties only.[51] While farmland value in these counties benefits from an increase in year-round precipitation, the response surface in this dimension is relatively flat. By contrast, the response surface is very steep with respect to an increase in temperature, and the adverse effects of a temperature increase strongly outweigh the beneficial effects of an increase in precipitation within the ranges considered.[52] The lower right panel of Figure 3 is based on the MNS preferred crop revenue coefficients estimated from all counties in the data set. The two response surfaces differ drastically not only in location (the MNS response surface implies that climate change raises rather than lowers farmland value in dryland, non-urban counties throughout the ranges considered) but also in slope, especially with respect to temperature. The MNS response surface suggests that an increase in temperature has only a small effect on farmland value and this (beneficial) effect actually increases with the increase in temperature.[53]

These empirical results provide strong support for our hypothesis that the farmland hedonic regression equation for dryland, non-urban farming areas is likely to be different than those for irrigated or urban areas, and that pooling all these areas without adequately controlling for the effects of irrigation and urbanization can produce biased and seriously misleading results.

For a complete national impact assessment, the estimates in Table 5 need to be modified in two ways. We need to take account of the impact of climate change on farming in irrigated and urban counties, and we need to allow for the fact that some counties may switch from dryland to irrigated farming (or vice versa) because of the effects of climate change. Our analysis of the factors determining the percent of farmland that is irrigated in each county in Appendix 1 provides some information that can be used for the latter adjustment. Based on the probit model in Appendix 1 Table 7, we estimate that global warming will lead to a net increase in irrigation. However, the increase is predicted to be quite small in the existing dryland, non-urban counties: overall, only 1.2% of the farmland in those counties is predicted to become irrigated as a result of the climate change scenario.[54] Given the small size of this change, the estimated $210 billion loss of farmland value is likely to be adequate for the dryland, non-urban counties without further adjustment.

With respect to estimating the impact of climate change in irrigated and urban counties, one way to proceed would be to use the regression coefficients that are the counterpart to those in Table 2, based on a regression using only the irrigated and urban counties. The resulting point estimates and confidence intervals are shown in Table 6. None of the estimates is significantly different from zero. The wide confidence intervals are likely due to specification error in the regression equation - as we noted earlier, in irrigated areas local precipitation is not a reliable measure of water supply.

Table 6: Change in Farmland Value in Irrigated and Urban Counties from Global Warming, Using Only Irrigated and Urban Counties in the Estimation; ($ billion, 1982)

| **Model** | **Point Estimate** | **95% Confidence Interval** | | |
|---|---|---|---|---|
| **Feasible GLS Model** | 56.4 | (-92.1 | ; | 225.2) |
| **Cropland Weights** | -28.8 | (-100.9 | ; | 60.3) |
| **Crop Revenue Weights** | 47.4 | (-89.6 | ; | 232.2) |
| **No Weights** | 30.8 | (-75.9 | ; | 139.3) |

Moreover, for the reasons indicated above, these estimates are likely to understate the true impact on irrigated agriculture because water supply in these areas is often subsidized and is generally priced well below replacement cost. Consequently, we believe that a different approach should be employed for assessing the economic impact of climate change in these areas that focuses explicitly on water demand and supply. Firstly, global warming is likely to cause some increase in the demand for irrigation water in the irrigated and urban counties. Based on the probit model in Appendix 1 Table 7, we predict that there will be an overall demand for an additional 7.5 million acres in these counties to become irrigated as a result of the MNS climate change scenario.[55] Moreover, the existing irrigated acreage in these counties is likely to require more water. Based on a lognormal regression of irrigation water use in these counties on climate variables, shown in Appendix 1 Table 8, we estimate that the climate change scenario will lead to an increased irrigation usage amounting to about 5.5 million acre feet on the acreage currently irrigated. The increased demand for irrigation due to higher ambient air temperature is likely to outweigh the effects of increased precipitation.[56] [57]

Secondly, global warming may lead to a net reduction in effective surface water supply in the irrigated counties unless there is significant additional investment in storage and conveyance facilities. The adverse effects of increased temperature on the timing of snowmelt, combined with the increased ET of watershed vegetation and increased evaporation from stored surface water, are likely to *outweigh* the benefits of increased precipitation in several major watersheds, including the Columbia River Basin and the Sacramento-San Joaquin River Basin.[58] In these regions, even with an increase in total annual streamflow, the timing of streamflow will change and, while there may be more winter streamflow, there will be less summer streamflow and therefore, absent additional investment in surface water storage, less water available to meet peak summer demands from agricultural and urban users.[59] In irrigated areas dependent upon surface water supply, given the combination of increased ET demand and reduced surface water supply, the most likely consequence of climate change is increased water shortage.[60]

In the event of a water shortage in irrigated counties, some of the shortfall would be met by increased conservation, crop switching, or land retirement, while some might be met by increased groundwater pumping, groundwater banking, water market purchases, and the development of new surface water supply. Whatever the response, there would be *some* economic cost.[61] A detailed assessment of the economic impact on irrigated agriculture lies beyond the scope of the present paper. Because the water resource systems are highly location-specific, this requires a case-by-case analysis. We are currently working on such an analysis for California, which alone accounts for about 22% of all irrigation water use in the U.S. An important factor in the cost of climate change there is how the legal and political system re-allocates water among the competing demands of agriculture (which currently uses about 80% of the developed water supply in California), urban uses, and environmental (instream) uses. The competition for scarce water resources makes it difficult to assess the economic impact on agriculture in isolation without also considering the impacts on other water using sectors. As a general conclusion, however, we believe it is likely that climate change will impose a net economic *cost* on agriculture in irrigated counties, whether in the form of higher costs for replacement water supply or lower profits due to reduced water supply.

As an alternative to the region-specific modeling and estimation which we believe is needed for irrigated areas, we can make a very rough preliminary calculation based on the estimate of 5.5 million AF in additional irrigation for the existing irrigated acreage. If this additional demand for irrigation is met by new surface water supplies, a conservative estimate of the cost is about $500/AF. If the demand is met by conservation or long-term water market purchases, a conservative estimate of the cost is about $175/AF. And, if it is met by land retirement, a conservative estimate of the value of lost farm production on marginal irrigated land is about $50/AF. This suggests that climate change in irrigated areas could impose a cost ranging from about $275 million to about $2.75 billion, depending upon how water is re-allocated in the face of increased scarcity. A more complete estimate, accounting for the cost of irrigating the additional 7.5 million acres in these areas, would of course be still higher.

Before closing, we should note that some recent implementations of the MNS model, by Mendelsohn et al. (1996) and Mendelsohn and Neumann (1999), have modified it in a couple of ways. First, the explanatory variables now include the diurnal and interannual variation in January, April, July and October average temperature and precipitation. Second, the dependent variable is now the total farm value in a county divided by the total area of the county, as opposed to the acreage of farmland. The models are still applied to the pooled sample of 2938 counties across the U.S.

When the variation terms are included in the model, Mendelsohn et al. (1996) find that "crop sensitivity to warming decreased." While we have been able to replicate this result in a supplementary appendix available upon request, we believe that several caveats should be noted. First, including the twelve variation terms substantially increases multicolinearity among the regressors - the condition number increases by a factor of 2.5. A consequence is that the confidence intervals for the estimated impact of climate change on aggregate farmland value are now 33-50% wider than when the variation terms are omitted. It still is the case that a Chow test rejects the hypothesis that the coefficients of the hedonic value equation are the same for dryland and irrigated counties. If one focuses on dryland counties, regardless of the weights chosen, the climate change scenario lowers the aggregate value of farmland, but the loss is smaller than when the variation terms are omitted; with the feasible GLS weights, the estimated loss is now $145 billion compared to $217 billion when the variation terms are omitted. However, this calculation follows Mendelsohn et al. (1996) in assuming that climate change affects only average temperature and precipitation but not the variation in temperature and precipitation. We believe this is questionable for two reasons. The diurnal temperature variations turn out to be positively correlated with the monthly average temperatures during the growing season, and the interannual variations in precipitation are positively correlated with the monthly average precipitations. Therefore, the postulated increases in monthly temperature and precipitation should be expected, ceteris paribus, to cause an increase in climate variation, which Mendelsohn et al. (1996) neglect. However, other things are not likely to be equal; the recent IPCC assessment indicates that there is a more than 90% chance of an increase in the frequency of extreme climate events, including intense precipitation (Intergovernmental Panel on Climate Change 2001). If the effects of increased variation were considered, the adverse impact of climate change on dryland farming would be greater.

When Mendelsohn and Neumann (1999) switch the dependent variable from farmland value per acre of farmland to farmland value per acre of all land in the county, the result is a reduction in the predicted benefit to agriculture, or an increase in the damage. But as before, we find a Chow test rejects the hypothesis that the coefficients of the hedonic value equation are the same for dryland and irrigated counties. If one focuses on dryland counties, the loss to agriculture from climate change almost doubles with the switch in dependent variable. However, this dependent variable implicitly assigns a value of zero to all land in the county that is not used as farmland. We consider this implausible. Some of the land is employed for urban uses, and is likely to have a higher value than some of the farmland in the county. In this case, while land conversion from agricultural to urban use produces an economic loss to farming, it presumably generates some *gain* to the overall economy. Hence, we do not consider it advisable to use this dependent variable.

## 6 Summary and Conclusions

The MNS hedonic approach "models irrigation in a reduced-form manner in which it is assumed that the availability of water in a region is a function of its climate and geography, including factors such as mean and seasonal precipitation and temperature" (Mendelsohn et al. 1996). We believe this holds reasonably well for dryland farming areas in the U.S., but not for irrigated areas; in irrigated areas the water supply is likely to be independent of precipitation and temperature in the growing area. Therefore, we believe it is incorrect to pool dryland and irrigated counties in a single hedonic regression equation and our empirical results bear out this contention. Here we summarize the implications for an assessment of the economic impact of climate change on U.S. agriculture.

We estimate that climate change could cause an economic loss to agriculture ranging from $5.0 billion annually under the unweighted model to $8.1 billion per annum under the feasible GLS model in the dryland, non-urban farming counties, in 1990 dollars, plus some additional quantum of loss in the irrigated counties. Our estimates have the same sign as the latest National Assessment, but are of opposite sign to the MNS estimate of an annual net gain amounting to about $2 billion, or the more recent estimate of Mendelsohn and Neumann (1999) of an annual gain of $24.3 billion, in 1990 dollars, both based on a Ricardian model of farmland value applied to all farming counties combined. We believe that the difference from our estimate, similarly based on a Ricardian model, is due to the pooling of dryland and irrigated counties. Interestingly, the original MNS estimate associated with the cropland weights is in closer agreement with some of the others in the literature, including ours, in both sign and magnitude. This is perhaps not surprising since the cropland weights appropriately in our opinion de-emphasize irrigated areas.

Finally, it should be noted that several caveats apply to our analysis, along with much of the rest of the literature here. Our impact estimates depend upon the specific hypothesized scenario of climate change, which may well turn out to be oversimplified both spatially and temporally. We consider the impact on U.S. producers but not consumers of agricultural commodities. Further we do not allow for changes in input and output prices beyond what is reflected in the existing cross-section equilibrium of land values nor for changes in technology or market structure.

Our analysis focuses on the economic effects of changes in temperature and precipitation, and not other parameters that could be affected by climate change such as solar radiation and $CO_2$ fertilization. As we noted earlier, the effects of $CO_2$ fertilization are still controversial (Wolfe and Erickson 1993). Existing results are based mainly on controlled agronomic experiments; other factors may be limiting in the field, and the fertilizing effect will apply also to weeds. Moreover, it appears that fertilization exhibits strong decreasing marginal productivity, with very small to zero benefit above twice the base pre-industrial level ($2XCO_2$). Assuming $CO_2$ levels continue to rise, the temperature effect seems likely to dominate beyond $2XCO_2$ if not sooner. Finally, a recent report by the National Research Council (2002) has argued that climate change might occur very abruptly when certain thresholds are crossed. In the case of abrupt change, farmers might not be able to adapt immediately and the Ricardian approach could then understate the economic impact.

# Notes

[1]Contributions to this literature include Smith and Tirpak (1989), Nordhaus (1991), Cline (1992), Fankhauser (1995), Tol (1995), Mendelsohn and Neumann (1999), and National Assessment Synthesis Team (U.S.) (2000).

[2]We transformed the estimate from 1982 dollars to 1990 dollars to make it comparable.

[3]Using an alternative set of weights for county observations, MNS estimate losses, not gains, to U.S. agriculture. Different weighting schema are discussed in Section 3 below.

[4]An important caveat is that both our analysis and the analysis by MNS do not account for other aspects of climate change besides temperature and precipitation, such as solar radiation and especially $CO_2$ fertilization. The $CO_2$ fertilization effect will likely increase yields and may reduce ET, but the magnitude of the effect remains uncertain and a matter of some controversy. Much of the existing evidence regarding plant response to $CO_2$ is derived from experiments under controlled conditions; how this translates to field conditions where crop productivity may be limited by factors other than $CO_2$ such as nutrients and water, and the fertility effect applies also to weeds, is not known (Wolfe and Erickson 1993). Further, it appears that the effects tapers off very sharply beyond a doubling of $CO_2$ in any event (Cline 1992).

[5]Because there are efficiency losses, the actual amount of irrigation water applied is larger than this. The typical irrigation efficiency in the area is about 70%, and the total irrigation application is about 43 inches (California Department of Water Resources 1986).

[6]For crops grown in the U.S., July is the month with the highest ET. Data on the percent of farmland irrigated come from the Bureau of the Census (1995); data on July precipitation are taken from MNS, as described below.

[7]The t-statisic for different sample means is 18.1.

[8]In Figure 1b and in the statistical analysis in Section 4 we use 5% of the farmland irrigated as the cutoff for defining dryland counties. We chose a low cutoff percentage in order to identify those counties where irrigation plays essentially no role in farming - since irrigated and non-irrigated farming are likely to require very different specifications of a farmland value equation, we want to isolate a relatively "pure" set of dryland counties. We conducted a sensitivity analysis and found that the results are robust for different subsets of counties in the East as long as we exclude the irrigated states in the West.

[9]The explanatory variables include climate variables (the average temperature and precipitation for the months of January, April, July and October); soil variables (salinity, moisture capacity, permeability, soil erodibility, and slope length); and socio-economic variables (per-capita income and population density).

[10]Of the 150 million acre-feet (AF) of irrigation water used annually in the U.S., about 63% is obtained from surface water and 37% from groundwater (Solley et al. 1998). The 17 western states where federal water projects are located account for 132 million AF of irrigation use (88%).

[11]Gleick (1987). A similar outcome is predicted for the Columbia River Basin: the increased temperature offsets the effects of increased precipitation, and leads to a reduced summer streamflow (Hamlet and Lettenmaier 1999).

[12]In addition, there are 25 federal water projects in the west that do not supply water for irrigation.

[13]Wahl's (1989) estimate is 14 cents on the dollar, but this is based on what he considers an optimistic assumption about the length of repayment periods. He estimates that the subsidy amounts to an average of about $1,900 per acre served by the Bureau.

[14]Local irrigation agencies in these states are mainly public districts or non-profit mutual water companies rather than for-profit commercial companies. Because they usually have a limited supply of water and sell at cost, there is often excess demand for irrigation water which leads to quantity rationing (Kanazawa 1993).

[15]Frederick and Schwarz (2000) mention several reasons why reservoir construction costs have risen in real terms. There are diminishing returns in safe yield produced by successive increments in reservoir capacity as evaporation losses begin to offset gains in yield from additional surface storage. As the best sites are developed, subsequent increases in storage require ever larger investments; in the 1920s a cubic yard of dam produced an average of 10.4 AF of storage capacity; this declined to 0.29 AF by the 1960s (U.S. Geological Survey 1984). In addition, there are increasing environmental constraints on new reservoir development.

[16]This is not the case when irrigation is supplied from groundwater. In the U.S., groundwater is typically self-supplied by individual farmers rather than collectively supplied through irrigation districts. Since energy for pumping is a large component of the cost and the capital involved is not unusually long lived, the cost of

groundwater supply is likely to be fully capitalized in farmland prices. However, since pumping depths (and energy prices) vary by an order of magnitude across farming areas, it would still be necessary to include in a hedonic regression a measure of pumping cost or depth to groundwater in order to avoid possible omitted variable bias.

[17]The discussion above focused on precipitation; temperature change is also likely to have a differential effect on dryland versus irrigated areas. In dryland areas, the main effect of temperature change is on water demand, rather than supply, because crop ET is highly sensitive to ambient air temperature. In irrigated areas, a change in temperature in the catchment areas also affects water supply through changes in both the timing of snowmelt and evaporation from stored surface water.

[18]See, for example, Freedman (1997) on the pitfalls of deducing causation via regression analysis based on observational data.

[19]Cropland differs from farmland because it excludes pasture, grazing and also woodland that is part of the farmer's operation. The dependent variable used by MNS is farmland value, not cropland value. In our view, using farmland value as the dependent variable, rather than cropland value, is more consistent with the logic of the Ricardian model because it allows for farmers to shift land between cropland, pasture, and forest as economic circumstance warrant.

[20]To compute these estimates, we replicated the MNS hedonic regressions using their data set, which was kindly provided to us by Robert Mendelsohn. We found that we could replicate the regression coefficients reported in their Table 3, but not their estimates of the impact of global warming reported in their Table 5. We believe that these contain an error. The dependent variable in their regression is the per acre market value of *farmland* in each county. To convert this to an aggregate county value, one should multiply by the number of acres of farmland in the county, which is what we do to obtain the estimate in our Table 1. We can replicate the MNS estimate in their Table 5 if we multiply by the number of acres of *cropland* in the county. The point-estimates reported by MNS in their Table 5 are \$-118.8 billion using cropland weights, and \$34.8 billion using crop revenue weights. Both these MNS estimates and our estimates in Table 1 truncate predicted farmland values at zero to rule out any negative values. This explains the slightly asymmetric shape of the distributions in our Figure 2. The truncation could be eliminated by adopting a logistic distribution for the random term in the regression model, as done by Xu et al. (1993); it would be difficult, however, to combine this with the statistical model of spatial correlation and heteroscedasticity that we present below.

[21]As noted above, the figure given by MNS in their Table 5 is different; it is a gain of \$34.8 billion.

[22]We used 100,000 bootstrap simulations to repeatedly estimate the hedonic regression model, and then calculate the predicted aggregate change in farmland value with the global warming scenario. To smooth the distribution of damages we used the non-parametric Epanechikov Kernel estimator with a bandwidth, $h$, equal to $h = \frac{0.9\sigma_d}{n^{0.2}}$, where $\sigma_d$ is the standard deviation of the change in county farmland value and $n = 100,000$ is the number of observations.

[23]Table 1 presents estimates of changes in farmland value for all counties and separately for dryland and non-urban counties versus irrigated or urban counties, using the classification of counties shown in Figure 1b.

[24]Perhaps the earliest of these studies is Haas (1924). Some summaries of the literature are provided by Renshaw (1958), Johnson and Haigh (1970), and Benirschka and Binkley (1994).

[25]We do not entirely understand the MNS argument for cropland weights since, while the dependent variable is the value per acre of farmland in the county, the weight is not the fraction of farmland in crops, as MNS seem to imply, but the fraction of all county land that is in crops.

[26]By contrast, the correlation coefficient between the percentage of farmland irrigated and the percentage of county in cropland, the weight MNS prefer less, is only 0.052. Thus, the danger of correlation between the cropland weights and the error term is much smaller than with their crop revenue weights.

[27]The other reason for the use of weighting in hedonic regressions is to correct for selection bias in the sample of observations; this use of weighting is discussed by DuMouchel and Duncan (1983) This is not an issue for MNS, however, because their sample covers most of the counties in the U.S. (2938 out of 3069 counties). The omitted counties are due to missing data.

[28]See, for example, Neary (1977).

[29]The major reference is Anselin (1988). An application to farmland value regressions is Benirschka and Binkley (1994).

[30] Kelejian and Prucha (1999) call this a Queen standardized weighting matrix.

[31]Our weights can be compared to the MNS weights as follows. It can be shown that, if $\rho = 0$ and the cropland area of every farm were the same in each county, $A'_{i,j} = A$ for all i and j, where $A'_{i,j}$ is the cropland (as opposed to farmland) in farm i in county j, our feasible GLS weights would be proportional to the number of farms in each county. If all U.S. counties are assumed to be of the same size, the number of farms in a county in turn might be roughly proportional to the percentage of county land in crops, which is the MNS cropland weights. On the other hand, if the revenues generated by each farm were the same for all farms, the MNS crop revenue weights would be proportional to the number of farms in each county, and thus roughly proportional to our weights. The latter, especially, seems to be a questionable assumption for the entire U.S. The average farm size in 1982 was 390 acres in California and 140 acres in Kentucky. The average sales generated by a farm in California ($151,479) was an even larger multiple of the sales in Kentucky ($23,385). Similarly, the correlation coefficient between cropland weights and the squared farmland shares is 0.59, while it is only 0.15 for the crop revenue weights.

[32]Bell and Bockstael (2000) use both GMM and ML estimation for a hedonic regression of urban home values and find that the results are very similar.

[33]The Census of Agriculture lists the entire farming area in Nassau County for the year 1982 as 1,879 acres. The average value per acre was $20,286, significantly higher than the national average of $784. An even more striking result holds for San Francisco County in California which only had 19 acres of farmland with an average value of $104,842 per acre.

[34]Our decision to drop urban and irrigated counties from the dryland farming regression is also supported by an analysis of the outliers from estimating a farmland value equation to all counties in the U.S. The analysis, described in Appendix 3, uses a Bayesian procedure developed by Zellner (1975) and Chaloner and Brant (1988) to detect outliers from the feasible GLS regression applied to the full MNS set of counties. 24 of the 2938 observations exhibit a posterior probability of being outliers; 19 of these are irrigated or urban counties.

[35]The average population density in the continental U.S. in 1984 was about 80 people per square mile; our definition of urban, therefore, is based on a cutoff density of five times the national average and excludes roughly 5% of the counties. Our results are not very sensitive to the specific definitions of irrigated or urban.

[36]We also excluded the few dryland and non-urban counties in the west to preserve a spatially connected set of observations for our estimate of spatial correlation.

[37]The MNS data is from the 1982 Census of Agriculture. We also replicated our analysis using the data from the 1987 Census of Agriculture and obtained similar results. We focus here on the 1982 data in order to highlight the comparison between our analysis and that of MNS. There was a sharp recession in U.S. agriculture during the 1980s, and farmland values fell by about 23% between 1982 and 1987; we prefer to avoid confounding our results with the shock caused by the recession.

[38]When calculating derivatives of the hedonic regressions, one should note that the variables have been demeaned. The derivative with respect to July precipitation turns positive only at a precipitation level substantially above the mean. Kaufmann (1998) and Quiggin and Horowitz (1999) have also made the point that several of the MNS coefficient estimates are agronomically implausible.

[39]For example, see Novotny and Olem (1994)

[40]The p-values for all three F statistics are less than $10^{-16}$. We obtained similar results using the crop revenue and cropland weights. Moreover, when we replicated the regression in Mendelsohn and Nordhaus (1999a) and bootstrapped the coefficients to generate probability distributions of climate change impacts on farmland value, the distributions were very similar to those shown in Figure 2. Allowing the intercept in the farmland value regression to differ between irrigated and non-irrigated counties, while forcing the slope coefficients to be the same, fails to reduce the diffuseness and heterogeneity in the distributions of climate change impacts.

[41]See Anselin and Florax (1995)

[42]The p-value of a type I error is again less than $10^{-16}$

[43]The sensitivity of our results to the proposed structure of heteroscedasticity is negligible. When the data was premultiplied with the cropland and crop revenue weights, all test statistics remain high and the estimate of $\rho$ for the dryland and non-urban counties was 0.435 compared to 0.438 under the squared farmland shares weights.

[44]The reported results use the estimate of $\rho$ that was obtained when the data was premultiplied by the squared farmland shares. As mentioned above, the estimates for $\rho$ are nearly identical when the data was premultiplied by the cropland or crop revenue model and the results in Table 4 differ only in the third digit.

[45]A further refinement might be to model the variance of the error terms $\mathbf{u}$ as the composite of a constant and the squared farmland shares. However, such a weighting structure cannot be estimated with the two-stage procedure utilized in this paper; given the results in Figure 3 below any improvement should be minor.

[46]The lower left panel in Figure 3 uses the same MNS coefficient estimate as Figure 2, but restricts the impact assessment to the 2186 dryland and non-urban counties.

[47]The linear specification allows us to easily separate the effect of each climatic variable on farmland values. The impacts attributable to a change in temperature are more than an order of magnitude larger than the ones attributable to the change in precipitation.

[48]These results are available upon request.

[49]We use the ratio of net farm income to aggregate farm value in 1982 as the conversion factor to translate the capitalized value into an annual impact. The ratio was 2.82% in 1982.

[50]Following USDA (1996), we used the Gross Domestic Product implicit price deflator to adjust farmland value to 1990 dollars.

[51]The axes have been reversed to provide a clearer picture of the damage surface; thus, the current climate conditions are characterized by the point (0,0) in the temperature-precipitation plane.

[52]This is consistent with the agronomic literature, which shows that crop ET is rather sensitive to ambient temperature and solar radiation during the growing season. Allen (2002) gives the elasticity of ET with respect to temperature as 0.2 - 0.5, and the elasticity with respect to solar radiation as 0.5 - 0.9. Based on a regression analysis of 216 weather stations reporting to the Solar Radiation Resource Information Center at the National Renewable Energy Laboratory, we find that average solar radiation is positively correlated with temperature. Hence, an increase in temperature is likely to be accompanied by an increase in solar radiation, both of which should impact ET.

[53]For the reasons noted above, this is hardly plausible agronomically.

[54] This estimate should be treated with caution. The current extent of irrigated agriculture in the U.S. reflects a history of development that occurred over more than a century and involved substantial fixed costs and economies of scale and agglomeration which introduced an important element of path dependence. A cross-section regression like that in Table 7 represents a snap-shot taken at a moment in time, and it will not necessarily provide a reliable prediction of how irrigation would expand in the U.S. over the next 50-100 years as global warming unfolds.

[55]This estimate is subject to the caveat noted in endnote 54 above

[56]For example, in the San Joaquin Valley, a uniform 5 degree increase in temperature would raise crop ET by about 0.4 - 1.1 inches, using the elasticity reported by Allen (2002); with 70% irrigation efficiency, this translates into an increased demand for irrigation water amounting to 0.6 - 1.5 inches. By contrast, a uniform eight percent increase in precipitation would increase the field water supply during the growing season by under 0.2 inches. Chen et al. (2000) and McCabe Jr. and Wolock (1992) reach a similar conclusion that global warming will cause a net increase in irrigation demand. Note that there would still be an increase in demand for irrigation water in these areas even if some farmland were converted to urban uses because there is a substantial *urban* demand for outdoor irrigation. In California, for example, almost half of all urban water use goes for outdoor irrigation, whether parks and golf courses, greenery surrounding suburban office buildings, or yards in people's homes (Hanemann and Dale 1988). This accounts for the sensitivity of urban water use to seasonal climate variation noted by Griffin and Chang (1991) and others.

[57]It is possible that, over some range, an increase in average temperature will result in higher expected crop yields. However, the relationship between temperature and yield is likely to be downward sloping beyond some point. Given concavity in the temperature-yield relationship, if the increase in temperature takes the form of more frequent occurrence of high-temperature spikes, the change in yield may be overstated by simply plugging in the change in average temperature. Moreover, there is likely to be substantial variation among individual crops and growing regions. In California, for example, some recent research suggests that an increase in temperature will tend to result in increased yields in the northern and coastal regions, but decreased yields in the San Joaquin Valley and the desert valleys. In addition, higher temperatures may also stimulate the growth, and extend the range, of weeds and pests.

[58]See Hamlet and Lettenmaier (1999); Leung and Wigmosta (1999); Gleick and Chalecki (1999); Jetton et al. (1996); and Lettenmaier and Gan (1990).

[59]The importance of the timing of precipitation relative to existing storage capacity cannot be overstated. When one just considers total annual precipitation and ignores the timing of runoff and storage, as in National Assessment Synthesis Team (U.S.) (2000) and Frederick and Schwarz (1999), this can produce a misleading impression of the impact on developed water supply.

[60]Gleick (2000) note that very little research has been done so far on the impact of climate change on groundwater basins and their recharge characteristics. In irrigated areas dependent upon groundwater, while climate change may or may not affect the groundwater supply, if it leads to an increase in irrigation demand there would still be an impact on groundwater in terms of declining aquifer levels and higher pumping lifts.

[61]In California, for example, recent water market transactions suggest a minimum cost of about $50/AF for water made available through agricultural land retirement, and about $175/AF for water made available through water district conservation measures such as canal lining.

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# Appendix 1 Which Counties are Irrigated and How Much Water Do They Use?

To explain why some counties are irrigated and others are not, we estimate a grouped probit model where the dependent variable is the percentage of farmland in the county that is irrigated and the explanatory variables are the suite of variables used by MNS. Since a probit model is inherently nonlinear and necessarily allows for increasing or decreasing marginal effects, we use only linear terms in the probit equation, which simplifies the interpretation of the probit coefficients. The model is estimated by maximum likelihood, and the coefficients are shown in Table 7.

Observe that higher temperatures in July increase the likelihood that farmland is irrigated as do lower April and July precipitation (less water is available) and higher January precipitation (more water can be stored for the next growing season). Higher April temperatures decrease the changes of irrigation. This might be due to the fact that higher temperatures in April allow an earlier planting cycle, decreasing the highest evapotranspiration requirements in July as the plant is already in a later stage of the planting cycle.

Table 7: Grouped Probit Regression of Percent of Farmland that is Irrigated

| Variable | Coefficient | Standard Deviation |
|---|---|---|
| Constant | -1.96 | 1.21E-04 |
| January temperature | 1.93E-02 | 3.50E-05 |
| April temperature | -2.80E-02 | 7.06E-05 |
| July temperature | 2.23E-02 | 5.51E-05 |
| October temperature | 2.78E-02 | 9.70E-05 |
| January precipitation | 7.65E-02 | 1.00E-04 |
| April precipitation | -3.50E-02 | 1.64E-04 |
| July precipitation | -6.34E-02 | 9.94E-05 |
| October precipitation | -6.92E-02 | 1.58E-04 |
| Per capita income | 9.94E-06 | 3.66E-08 |
| Population density | 1.47E-04 | 5.04E-07 |
| Latitude | 2.25E-02 | 7.78E-05 |
| Altitude | 1.37E-04 | 1.55E-07 |
| Soil salinity | -1.27 | 1.19E-03 |
| Flood prone | 0.358 | 3.80E-04 |
| Wetland | 1.83 | 1.20E-03 |
| K factor | 1.72 | 1.92E-03 |
| Slope length | 0.147 | 4.22E-05 |
| Sand | 0.301 | 4.49E-04 |
| Clay | 4.02E-02 | 2.21E-04 |
| Moisture capacity | 4.29E-05 | 3.15E-07 |
| Permeability | 1.59E-05 | 1.43E-08 |

The probit model provides an estimate of the percentage of a county that is irrigated. In a second step we examine the *quantity* of irrigation water used in each county with a log-normal regression. The dependent variable in the regression equation is the log of the quantity used (in feet) obtained from U.S. Geological Survey for each of the 525 irrigated counties. We use the same set of explanatory variables as MNS.

A five degree Fahrenheit increase in temperature and an eight percent increase in precipitation translates into an expected additional demand of 5.5 million acre feet of water for the 525 irrigated counties.

Table 8: Log-normal Regression of Irrigation Quantity used in the 525 Irrigated Counties

| **Variable** | **Coefficient** | **t-value** |
|---|---|---|
| Constant | 16.8 | ( 4.91) |
| January temperature | -6.98E-02 | ( 3.15) |
| January temperature squared | 5.58E-04 | ( 1.22) |
| April temperature | 0.374 | ( 3.29) |
| April temperature squared | -3.80E-03 | ( 3.79) |
| July temperature | -0.349 | ( 3.30) |
| July temperature squared | 2.36E-03 | ( 3.13) |
| October temperature | -0.217 | ( 1.36) |
| October temperature squared | 2.34E-03 | ( 1.65) |
| January precipitation | 0.197 | ( 4.05) |
| January precipitation squared | -1.60E-02 | ( 4.82) |
| April precipitation | 0.249 | ( 2.32) |
| April precipitation squared | -2.21E-02 | ( 1.60) |
| July precipitation | -0.374 | ( 5.32) |
| July precipitation squared | 3.73E-02 | ( 4.46) |
| October precipitation | 6.74E-02 | ( 0.78) |
| October precipitation squared | 2.09E-02 | ( 1.69) |
| Per capita income | 1.50E-05 | ( 1.61) |
| Population density | 9.10E-04 | ( 7.42) |
| Population density squared | -1.12E-07 | ( 3.05) |
| Latitude | -4.68E-02 | ( 2.18) |
| Altitude | -8.35E-05 | ( 2.01) |
| Soil salinity | -0.735 | ( 2.59) |
| Flood prone | -0.191 | ( 2.11) |
| Wetland | 0.22 | ( 0.88) |
| K factor | -0.315 | ( 0.66) |
| Slope length | 5.29E-02 | ( 4.77) |
| Sand | -5.56E-02 | ( 0.62) |
| Clay | 7.81E-02 | ( 1.37) |
| Moisture capacity | 2.65E-05 | ( 0.24) |
| Permeability | 2.16E-06 | ( 0.55) |

# Appendix 2 Construction of the Squared Farmland Shares

The optimal set of weights to correct for the heteroscedasticity of the error terms, the squared farmland shares, are derived in equation (4) on page 17. Unfortunately this variable is not directly available form the Census of Agriculture. Due to privacy restrictions, it is impossible to obtain the size of each individual farm. This appendix describes the construction of a proxy for squared farmland shares.

The Bureau of the Census (1995) lists the number of farms that fall within a certain class size, i.e., the number of farms with an area between 1-9 acres, 10-49 acres, 50-69 acres, 70-99 acres, 100-139 acres, 140-179 acres, 180-219 acres, 220-259 acres, 260-499 acres, 500-999 acres, 1000-1999 acres and over 2000 acres. We construct a rough proxy variable by estimating the log-normal distribution of farm size for each county and extrapolating the farms that fall within a defined class size (i.e., belong to same range of acreage) as published in the Census of Agriculture.

The 12 categories of farmland sizes can be written as $[a_k, b_k)$ for k=1...12. Let $F_{(\mu,\sigma)}(x)$ denote the cumulative log-normal distribution as a function of the mean $\mu$ and the standard deviation $\sigma$ of the normal distribution. The probability that a farm in county j falls within a given class is simply the difference in the cumulative distribution of the two border points of the class, i.e., $F_{(\mu_j,\sigma_j)}(b_k) - F_{(\mu_j,\sigma_j)}(a_k)$.

Using the number of farms $N_{k,j}$ for each class k=1..12 and county j, we maximize the log-likelihood function for each county $l_j(\mu_j, \sigma_j)$

$$\max_{\mu_j \sigma_j} l_j(\mu_j, \sigma_j) = \sum_{k=1}^{12} N_{k,j} \quad log \left[F_{(\mu_j,\sigma_j)}(b_k) - F_{(\mu_j,\sigma_j)}(a_k)\right] \tag{12}$$

In a second step we approximate the size of the $N_{k,j}$ individual farms in category k in county j by uniformly extrapolating the $N_{k,j}$ farms over the cumulative distribution between $F_{(\mu_j,\sigma_j)}(a_k)$ and $F_{(\mu_j,\sigma_j)}(b_k)$. For example, if there are 5 farms in the 70 to 99 acres interval representing the 20% and 25% quintile of the log-normal distribution, we spread the number of farms uniformly between the 20% and 25% quintile, i.e. the farms represent the 20.5%, 21.5%, 22.5%, 23.5%, and 24.5% quintiles. The only exception to this rule is the open-ended interval for farms with more than 2000 acres. If a lot of farms fall within this category, the linear interpolation would result in interpolated farms too close to the 100% quintile (which implies an infinite acreage). Therefore, if the total acreage of the largest category is available (it is listed if more than three farms fall within the category) we include a constant spacing between the 2000-acres quintile and each subsequent farm subject to the constraint that the sum of the acreages of all interpolated farms equals the actual total farm acreage within the open-ended category. If three or less farms are in the largest category we use the procedure of uniform extrapolation. In a third step we calculate the sum of squared farmland shares $s_{i,j}$ for the $N_j$ extrapolated farms in county j.

# Appendix 3 Outlier Analysis

This appendix outlines the Bayesian outlier analysis of Zellner (1975) and Chaloner and Brant (1988). Given the standard linear regression model in equations (6) - (8), where $\mathbf{X}$ is a (NxK) matrix and $\mathbf{x}_i'$ is the (1xK) submatrix for observation i,

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} \tag{13}$$

$$y_i = \mathbf{x}_i'\boldsymbol{\beta} + \epsilon_i \tag{14}$$

with i.i.d. normal error term $\boldsymbol{\epsilon}$ and a diffuse prior, the posterior distribution of the error terms $p(\boldsymbol{\epsilon}|\mathbf{y}, \sigma)$ will be multivariate normal while the marginal posterior distribution of the standard deviation $p(\sigma|\mathbf{y})$ will be an inverted gamma distribution. These posterior probabilities can then be used to calculate the probability that $|\epsilon_i|$ is larger than $\gamma\sigma$ where $\gamma$ is a constant. The value of $\gamma$ can be chosen such that the prior probability of no outlier is large. We follow Chaloner and Brant and set $\gamma = \Phi^{-1}\left(\frac{1}{2} + \frac{1}{2} * 0.95^{\frac{1}{N}}\right)$ to ensure that the prior probability to observe *no* outliers is 95%. ($\Phi$ denotes the cumulative standard normal distribution). Using the OLS estimate $\widehat{\boldsymbol{\beta}}$ as well as the OLS estimates of the variance $s^2$ we can write

$$p(\epsilon_i|\mathbf{y}, \sigma) \sim N\left(\widehat{\epsilon}_i = y_i - \mathbf{x}_i'\widehat{\boldsymbol{\beta}}, \sigma^2\mathbf{x}_i'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{x}_i\right)$$

and utilizing the changes of variables technique where $\tau = \frac{1}{\sigma^2}$

$$p(\tau = \frac{1}{\sigma^2}|\mathbf{y}) \propto \tau^{\frac{N-K}{2}-1}e^{-\frac{(N-K)s^2}{2}\tau}$$

Hence the probability that the absolute value of the error term of observation i is greater than $\gamma\sigma$ conditional on $\sigma$ will be

$$\begin{aligned} p(|\epsilon_i| > \gamma\sigma|\mathbf{y},\sigma) &= p(\epsilon_i > \gamma\sigma|\mathbf{y},\sigma) + p(\epsilon_i < -\gamma\sigma|\mathbf{y},\sigma) \\ &= 1 - \Phi\left(\frac{\gamma\sigma - \widehat{\epsilon}_i}{\sigma\sqrt{\mathbf{x}_i'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{x}_i}}\right) + \Phi\left(\frac{-\gamma\sigma - \widehat{\epsilon}_i}{\sigma\sqrt{\mathbf{x}_i'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{x}_i}}\right) \\ &= 1 - \Phi\left(\frac{\gamma - \widehat{\epsilon}_i\sqrt{\tau}}{\sqrt{\mathbf{x}_i'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{x}_i}}\right) + \Phi\left(\frac{-\gamma - \widehat{\epsilon}_i\sqrt{\tau}}{\sqrt{\mathbf{x}_i'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{x}_i}}\right) \end{aligned} \tag{15}$$

The probability that $|\epsilon_i|$ is greater than $\gamma\sigma$ is then

$$p(|\epsilon_i| > \gamma\sigma|\mathbf{y}) = \int_0^\infty p(|\epsilon_i| > \gamma\sigma|\mathbf{y},\sigma = \frac{1}{\sqrt{\tau}})p(\tau|\mathbf{y})d\tau \tag{16}$$

A two-stage procedure is used. In the first stage the data are premultiplied by $\mathbf{P}$ and $\mathbf{I} - \widehat{\rho}\mathbf{W}$ to obtain a data set with i.i.d. error terms. We then evaluate the integral in (16) using Simpson's rule with 10,000 grid points. 24 out of the 2938 observations exhibit a posterior probability $p(|\epsilon_i| > \gamma\sigma|\mathbf{y})$ greater than the prior probability $2\Phi(-\gamma)$.